Aggregators Efficiency in Distributed Power Networks

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***Abstract*—Fully distributed smart power grids approaches are increasing in the energy sector. A prosumer (producer-consumer) is a user that not only consumes electricity, but can also produce and store electricity. This paper focuses on power market models in which prosumers interact in a distributed environment during the purchase or sale of electric power. In this paper, we propose an hierarchical distributed model, which is based on reinforcement learning and optimization. Different types of prosumer are able to intelligently buy energy from, or sell it to, the power market. Our simulation results show that the integration of the aggregator in the power grid help to reduce the peak energy consumption and to lower the electricity cost for the population of prosumers.**

Keywords–distributed power networks, prosumers, aggregators, optimization, reinforcement learning.

I. INTRODUCTION

Exploratory researchs in the field of smart grid are increasing in the renewable energy sector. As energy efficiency and clean energy technologies become more common, system challenges require to rethink traditional paradigms of energy system planning and operation. A clean energy revolution is taking place worldwide. We can distinguish between two types of electricity power management systems: the centralized and the decentralized power management system [4], [5], [6], [7], [9].

The centralized power management system is currently used in many countries [1], [2], [8]. The feature of the centralized model is that at the physical layer, the grid is designed for a one-way flow of the electricity. More precisely, from the top where the electricity is generated from large power plants and transported to local substations, to the bottom which is the final stage in the delivery of electricity to end users. Moreover, at the power market layer the wholesale power market of this model can be subdivided into two category [3]: integrated (or pool) market and unbundled (or forward) market.

The idea behind the decentralized power management system is to exploit the increasing integration of decentralized energy resources (DER) into the distribution network [1], [2], [8], [12], [15], [16], [17]. DER systems are modern technologies based on solar, wind, geothermal, water, biomass, biofuel or other renewables energy resources. More precisely, they are small or mid-scale power generation technologies (typically in the range of 3KW to 10 MW). A prosumer (producer-consumer) is a user that not only consumes electricity, but can also produce and store electricity. Establishing clean or renewable energy sources involves the problem of adequate management for networked power sources. This is due to intermittency of renewable energy source during the electricity generation and to the variability of prosumer consumption/production.

In [13], the authors propose a methodology to quantify the quantity of ramping load reserves a priori. However, it is assumed therein that the probability density function of imbalances is invariant, which may not be the case of current energy systems. The work [14] studies scheduling techniques for storage devices using global information between the entities.

A. *DIPONET: a grid of micro-grids*

In this paper, we introduce a distributed power negotiation concept that enables the energy balancing in the entire power network and we term it DIPONET. Our approach is more dynamic since it provides the consumer/prosumer a more efficient way to interact in the distributed power network. The DIPONET approach is based on the previous project DEZENT [4], [5] . The limitation of the producer/consumer in the previous project is that it only make use of reinforcement learning when buying/selling energy from/to the power market. The consumer in that approach is static in the sense that it is not able to anticipate or to delay energy consumption. Moreover at the power market layer, a negative bidding strategy used by the static producer/consumer was affecting its portfolio.

TABLE I. Notations

Symbol	Meaning
$[1,2,\cdots,T]$	time horizon of an entire day
Q_t	the energy profile of an entire day. $[q_1,\cdots,q_t]$
$k \in \mathbb{Z}$	maximum energy variation
$x_t \in \mathbb{Z}$	the energy variation at time t, $-k \leq x_t \leq k$.
R_{max}	maximal energy reserve capacity $R_{max} : \mathbb{N}$
R_0	initial energy reserve capacity $R_0 : \mathbb{N}$
R_t	state of the energy reserve at time t, $R_t : \mathbb{N}$
$o : \mathbb{Z} \to \mathbb{R}$	additional cost. if $0 \leq x$ then $o(x) = x$ else $x \leq o(x) \leq 0$.
A	the the strategy space of the consumer/producer
s_t	negotiation strategy at time t, $s_t \in A$
$P(t,s)$	the value of the payoff associated to action s at time t.
$r(t,s)$	the realized payoff associated to action s at time t.
$\alpha \in \mathbb{R}$	$0 < \alpha \leq 1$
m	the number of prosumer of the aggregator

B. *Contribution*

The novelty of our approach is that it combines both distributed learning and optimization to predict supply/demand and storage in a more efficient way. More specifically we use reinforcement learning to adapt prosumer's price strategy at the power market and dynamic programming to predict future outcomes. The learning accounts for the fact that the power producer/consumer will need to use his/her best strategy when buying/selling energy quantities from/to the power market. The dynamic programming approach is due to the fact that a short term optimization might not be suitable in the event that a

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power consumer needs to plan his/her energy consumption over a period of a day, a week or even a month.

We show that a consumer with DIPONET scheme gets a lower cost than the one using DEZENT scheme. We then introduce the notion of aggregator in the distributed power market DIPONET. We show, through experimental study, that the aggregator is able to reduce the peak energy consumption of the grid. In our setup, an aggregator is composed of a set of prosumers. We distinguish two type of aggregator models: (i) the prosumers can share information about their expected energy price, (ii) and in the other the information is not shared. Interestingly we show that in both aggregator models the additional energy needed by the grid operator can be made available by the aggregator during the under supply period and peak load.

The rest of the paper is organized as follows. In the next section, we describe the prosumer planning methodology with both optimization and learning. In Section III we present the effect of the aggregator in the distributed power networks. Experiments and numerical results are presented in Section IV. Section V concludes the paper.

The notations used in the article are given in Table I.

II. PROSUMER PLANNING AND ADAPTATION MODEL

The power grid (see Figure 1) of interest consists of a bottom-up multi-level micro-grids architecture which is subdivided into 4 levels. The first level (0.4 kV) is a low-range network covering subdivisions (a neighborhood). The second level (10 kV) is a medium-range area network covering a suburb (regional grid). The third level (110 kV) is a long-distance energy transport network. Finally in the fourth level (380 kV) the electricity is produced from large power plants (coal, gas or nuclear). Power needs of prosumers are covered through alternative energy sources within the first 2 layers and additional power needs will be covered at the latest by the fourth level.

At the power market layer, we consider a multi-stage negotiation system through which the energy produced by micro-grids (at various tiers) are auctioned to/by the prosumers. The balancing of demand and supply between participants is carried out through balancing group managers (BGMs) which are located in different network layers and operate in parallel on each grid. The BGM balances the supply and the demand of electricity between a producer and a consumer who have submitted a similar bid.

A prosumer in such a power grid can be viewed as user who has the ability to independently modify his/her power requirements optimizing his cost (see Figure 2). In our model, we believe that independent planning by the prosumers may improve significantly the matching between production and consumption in the power grid. In practice, this could mean to help balancing the power market, since the price will favor low consumption/high production when the cost is high and vice versa. Moreover, our approach is not centralized and, in this sense, is different from demand side supply management. The idea is to exploit the (limited) ability of prosumers of planning in an autonomous way their consumption/production. Hence, they do not sign any contract leaving the planning to others: our independent consumer planning is a local matter involving only one prosumer.

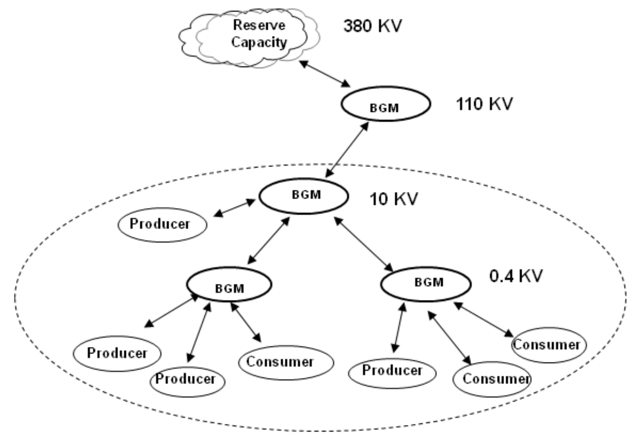

Figure 1. Power grid and associated agents [4].

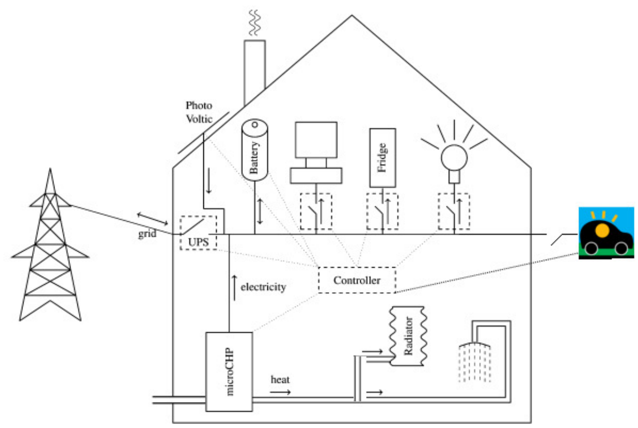

Figure 2. Model of a smart house energy consumption/production.

A. Control strategy of the Prosumer in the DIPONET approach

The challenge of the prosumer is to make elastic the demand for, and the supply of, electricity in order to optimize its energy cost based on power market conditions and on suitable constraints on their power consumption. Prosumer strategies are concerned with two separate phases. On one hand, prosumers should compete on the DIPONET power market: they should negotiate a deal with a close partner, thus achieving a better price. On the other hand, they should concentrate as much as possible their energy consumption in the periods when the prices are more convenient. For clarity we will use a consumer oriented terminology, but most of the discussion could be dualized.

We now described the combined scheme DIPONET.

Step 1: Reinforcement learning

At the end of a negotiation, the final achieved price by the consumer is normalized according to the frame size of the negotiation. Then, the temporal difference method of Sutton [10], [11] is used to derive the payoff of the negotiation strategy currently executed.

$$P(t+1,s) := P(t,s) + \alpha\left(r(t,s) - P(t,s)\right); \qquad (1)$$

Step 2: Optimization
For clarity we consider the case of a consumer. The consumer is characterized by the class of energy variation profiles (s)he can adopt during the day.

Controllable inputs: we denote by $x(t)$ the vector of controllable inputs of the consumer. The consumer has the ability to increase/decrease its energy consumption.

State of the consumer: the state of the consumer is given by the level of the energy reserve R_t.

Objective function: the objective of the consumer is to minimize the electricity cost achieved at the end of the day.

$$\max_{x(t),t=1,\ldots,T} \sum_{t=1}^{T} (o(x_t)+q_t)P(t,s) \tag{2}$$

Constraints
(i) summing up all the variations from the beginning of the day to any time, we cannot exceed a lower and an upper bound of the energy reserve. This constraint accounts for available energy storage media, like electric vehicle batteries or thermic accumulations due to anticipated heating, or delayed air conditioning.

$$\forall\ 1 \le t \le T,\ 0 \le R_0 + \sum_{t=1}^{T} x_t \le R_{max} \tag{3}$$

(ii) the sum of all the energy variations in the whole day for the consumer is zero, i.e. if in some slot the variation is positive, in some other slot it must be negative.

$$\sum_{t=1}^{T} x_t = 0 \tag{4}$$

Proposed algorithm: we propose an efficient dynamic programming algorithm for planning the energy consumption/production. The control algorithm of the consumer has three inputs: (i) the definition of the class of allowed profiles Q; and (ii) the cost of a unit of energy which is the result of the negotiation in each time step of the previous day. Hereafter, the optimization problem and the proposed dynamic programming algorithm used to solve it are defined.

Let $Z_t(Y_t) : \mathbb{R} \cup \{\infty\},\ t = 1,\ldots,T,\ 0 \le Y_t \le R_{max}$ be the optimal energy costs for time step $1,\ldots,T$, when the final energy reserve at time t is Y_t. Here $Z_t(Y_t) = \infty$ if energy reserve Y_t cannot be achieved at time step t. Thus $Z_0(Y_0)$ (no slot has elapsed yet) is everywhere ∞ except for $Z_0(R_0) = 0$.

Subproblems

$$Z_t(Y_t) = \max_{x_1,\ldots,x_t} \sum_{i=1}^{t} (o(x_i)+q_i)P(i,s)\ ,\ t = 1,\cdots,T \tag{5}$$

$$\forall i'\ \ 1 \le i' \le T,\ 0 \le R_0 + \sum_{i=1}^{i'} x_i \le R_{max} \tag{6}$$

$$R_0 + \sum_{i=1}^{t} x_i = y_t \quad 0 \le y_t \le R_{max} \tag{7}$$

Dynamic programming

$$Z_t(Y_t) = \max_{\substack{-k \le x_t \le k \\ 0 \le Y_t - x_t \le R_{max}}} Z_{t-1}(Y_t - x_t) + (o(x_t)+q_t)P(t,s) \tag{8}$$

$$Z_0(Y_0) = \text{ if } Y_0 = R_0 \text{ then } 0 \text{ else } \infty \tag{9}$$

$$Z_T(R_0) = Z \tag{10}$$

The value of Z_t at time t is computed sequentially in terms of Z_{t-1} by looking backwards for $Z_t(Y_t)$ to the optimal energy costs at slot $t-1$ for eligible values $Y_t - x_t$ of the energy reserve. Finally, an *optimal strategy* S is any sequence $S = (\widehat{x_1},\widehat{Y_1}),\ldots,(\widehat{x_T},R_0)$ such that the values of $\widehat{x_t}$ and of $\widehat{Y_{t-1}}$ are computed backwards from $\widehat{Y_t}$, $t = T\ldots,1$, by letting $\widehat{Y_T} = R_0$, the final reserve being R_0. Formally: optimal strategy

$$Z_t(\widehat{Y_t}) = Z_{t-1}(\widehat{y_t} - \widehat{x_t}) + (o(\widehat{x_t})+q_t)P(t,s)\,, \tag{11}$$

$$\widehat{Y_{t-1}} = \widehat{Y_t} - \widehat{x_t} \tag{12}$$

$$\widehat{Y_T} = R_0 \tag{13}$$

The time and space complexity of the algorithm are $O(TR_{max}k)$ and $O(TR_{max})$ respectively.

In section IV, we compare the behavior, in terms of energy cost minimization, of a consumer in our approach with that of a consumer of the DEZENT approach

III. Aggregator optimization model

We study the effect of an aggregator in the DIPONET power market. An aggregator in our model is defined as a collection of prosumers. In the proposed approach, each prosumer is neutral in the sense that it essentially neither consumes nor produces energy, as it can only sell in the power market the energy previously bought and stored. Actually, a prosumer consumes a little amount of energy, due to the overhead of the energy storing processes. Thus the behavior of the virtual prosumer is similar to that of a rechargeable battery. Only a real prosumer could combine the effect of a virtual prosumer with that of a producer and a consumer.

We define two types of aggregator: (i) a decentralized aggregator which consists of a number of prosumers running in parallel. Those agents do not exchange with each other the information about their energy achieved price. (ii) Centralized aggregator in which prosumers share (and therefore use) the same price information for the bidding and optimization phase. The objective of the aggregator in this case is to maximize its portfolio at the end of the day.

Decentralized aggregator: each virtual prosumer (of the aggregator) exploits the control model defined in section II-A.

Centralized aggregator: let m be the number of prosumer globally controlled by the aggregator.
Controllable inputs: we denote by $[x_1(t),\cdots,x_m(t)]$ the vector of controllable inputs of the aggregator. The aggregator has the ability to buy or sell energy in the power market.

Uncontrollable inputs: the uncontrollable input are the same as in the case of the costumer.

Aggregator state: $X_{Aggr}(t) = \sum_{i=1}^{m} x_i(t)$

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TABLE II. Non stationary DIPONET environment setup

Architecture	Negotiation Level	1
	BGM on Level 1	1
	Clients	23
	Producers (50 – 350 KW)	10
	Consumers (50 – 300 KW)	10
	Prosumers (50 – 300 KW)	3
Electricity price	Day duration: 60 slots (24 hours)	
	Profile cost of the electricity (free market)	
prosumers environment	Producers: Gaussian distribution 1	
	Consumers: Gaussian distribution 2	
Energy reserve	finite capacity	
	prosumer initial level: 0	
Controller	Class of consumption profiles	
	Planning phase: optimization	
Simulations	Duration: 3 days	
	Test: non stationary environment	

Objective function: the objective is to maximize the the gain of the portfolio at the end of the day.

$$\max_{[x_1(t),\cdots,x_m(t)],t=1,\ldots,T} \sum_{i=1}^{m}\sum_{t=1}^{T}(o(x_t)+q_t)P(t,s) \tag{14}$$

Constraints: in our model, the allowed profiles of the aggregator must satisfy the following constraints:

(i) the energy variation in a time step for any prosumer belonging to the portfolio of the aggregator has a lower and an upper bound;

$$\forall\ i \in \text{Aggr}, \forall\ 1 \le t \le T,\ 0 \le R_0 + \sum_{l=1}^{t} x_{il} \le R_{max} \tag{15}$$

(ii) the sum of the all the energy variations in the whole day for the aggregator is zero. Notice that at the end of the day this condition must be different from zero when considering only one prosumer belonging the portfolio of the aggregator.

$$\sum_{i=1}^{m}\sum_{t=1}^{T} x_{it} = 0 \tag{16}$$

(iii) summing up all the variations from the beginning of the day to any time, we cannot exceed a lower and an upper bound. Let m be the number of prosumers of the aggregator

$$\forall\ 1 \le t \le T,\ 0 \le \sum_{i=1}^{m}(R_0 + \sum_{l=1}^{t} k_{il}) \le mR_{max} \tag{17}$$

The algorithm used by the central aggregator is similar to that of section II-A except for the fact that: (i) the achieved price used in the algorithm is the weighted average of all the prosumer of its portfolio; (ii) the constraints of the problem are both local and global and (iii) the aggregator finally allocates the energy profile for each prosumer.

IV. SIMULATION STUDIES

The setup of the space of the experiments is based on the available DIPONET and DEZENT simulator and on the implementation of the two types of aggregator. It depends essentially on three parameters: (i) the free market power cost, which can exhibit high or low variance: for this we chose real data from the day ahead market prices of Switzerland (date: March 9, 2013); (ii) the prosumers environment, namely heavy production or heavy consumption, in which the total amount of the electricity produced in the subnet is respectively greater than or less than, the total amount needed in the subnet. In the heavy consumption situations, the additional, needed power is made available at the large power plant level, at a price which depends on the time of the day. Analogously for the heavy production situations. In all these cases, the profile cost of the electricity at the global level (namely at the large power plant level) was the same for all days; (iii) the available energy reserve capacity of the virtual prosumers characterizing the aggregator is considered finite. The experiments were conducted on the NYUAD cluster at the division of Engineering laboratory, simulating a 3 days service period (see Table II). Here the last day has been considered, since in this way transitory effects are minimized.

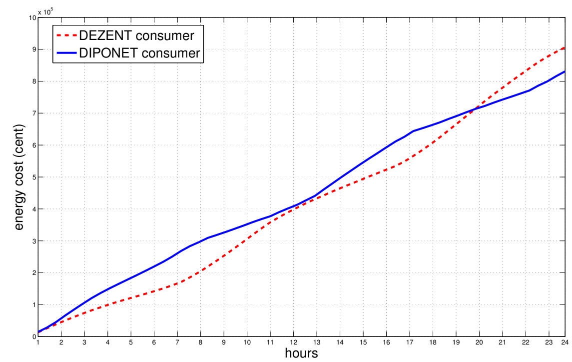

Figure 3. DIPONET vs DEZENT.

DIPONET vs DEZENT: in the first experiment we compare the behavior of a consumer in the DEZENT approach with that of our approach. The comparative study is based on the total cost of the electricity paid at the end of the last day. We recall that the consumer in DEZENT only make use of reinforcement learning while the consumer in the DIPONET approach uses both reinforcement learning and optimization. In Figure 3 the consumer in DEZENT (dashed curve) has spent more than the DIPONET consumer (solid curve). The saving of the DIPONET consumer is about 8,23%. This is due to the fact that the DIPONET consumer is able to anticipate or delay energy consumption thanks to its flexibility.

Aggregator models: in the second experiment comparative studies were based on the total cost of the electricity paid at the end of the last day by the consumer population and on the profit realized by the aggregators. Figure 4 synthesizes the optimal controller of the one prosumer of the centralized aggregator. The two upper curves of Figure 4 represent the unitary cost of energy as resulting from the negotiation phase at day 2 (solid curve) and at day 3 (dashed curve). The difference between the two upper curves gives an idea of the possible variations between the outcomes of different negotiations. Notice that the profile of the global energy cost and the context of competing prosumers is the same in both days. The lower dashed curve (respectively lower solid curve) represents the result of the optimization algorithm applied to the curve of day 2 (respectively of day 3). The curves plot the sum (from the beginning of the day) of the suggested variations: according to

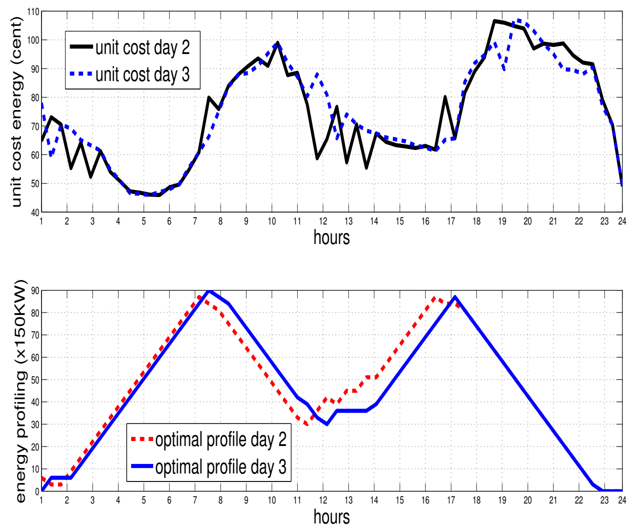

Figure 4. Optimization model of one prosumer.

the constraints we assumed on the virtual prosumers profiles, the sum of the variation must be not greater than the aggregates reserve capacity and should end up at 0. Notice that the controller correctly suggests variations which are opposite wrt. the negotiated cost.

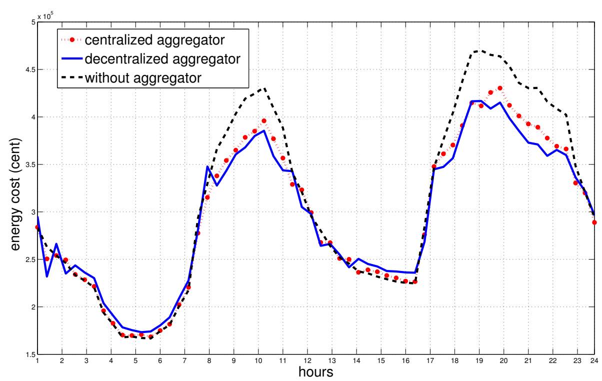

Figure 5. Energy cost achieved by the consumer population.

Figure 5 reports the result of the placebo test on the behavior of the consumer population. In Figure 5, the upper dashed curve represents the energy cost achieved in each hour by the entire population when there is no aggregator in the power market. Analogously, the middle bullet curve represents the case in which the centralized aggregator is active and the lowest solid curve the case in which the decentralized aggregator is active. The observation we have is that the consumers population when the aggregator is active has spent less during peak energy consumption period.

In Figure 6, the final cost achieved at the end of day 3 by the population of consumers in which the aggregator was active (solid curve for the decentralized approach and bullet curve for the centralized approach) is less than the case in which there was no aggregator (dashed curve). This positive effect is due to the introduction of an aggregator. The two curves when the aggregator is active are overlapped and this is due to the fact the available reserve charactering the aggregators are the same in both cases. The percentage of global energy cost reduction is about 3,2%.

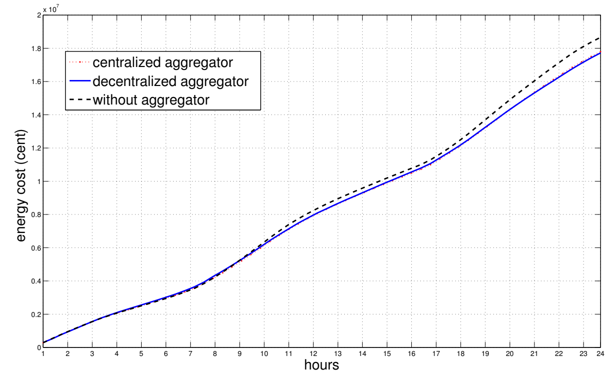

Figure 6. Energy cost at the end of the day achieved by the consumer population.

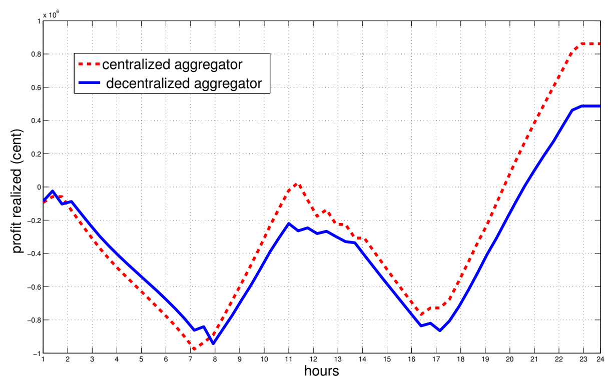

Figure 7. Aggregators: profit realized.

In Figure 7 we compare the actual profit of the two aggregator approaches. The solid curve reports the energy cost (actual profit) realized by the decentralized aggregator in the power market. The profit is given by the sum of the entire profit realized by the virtual prosumers characterizing the aggregator. Analogously, the dashed curve reports the actual profit of the centralized aggregator. The profit in the centralized case is given by the sum of energy cost achieved in every time slot. There is a remarkable difference between the two gains and the centralized aggregator exhibits a superior behavior. This is due to the fact that the centralized aggregator uses cooperative informations of virtual prosumer characterizing its portfolio. The information about the difference between the two gains of Figure 7 can be well studied if we compare the actual profit of each aggregator with its expected one.

In Figure 8, the dashed curve represents the expected profit of the decentralized aggregator at the end of day 3. The curve is computed by assuming known in advance the energy cost. That curve has been obtained by summing up all the energy

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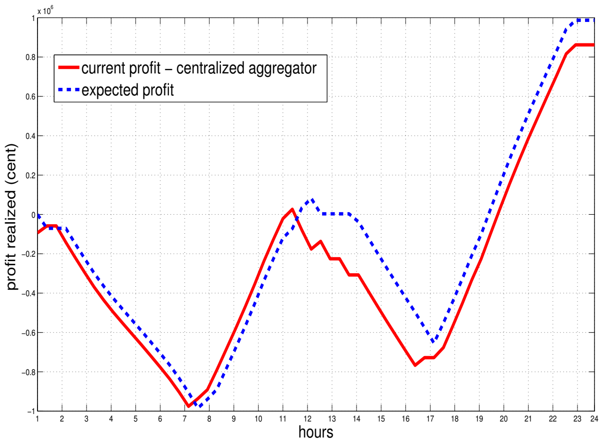

Figure 8. Centralized aggregators, expected cost vs real cost.

costs of the optimal profile of day 3 of the virtual prosumers.

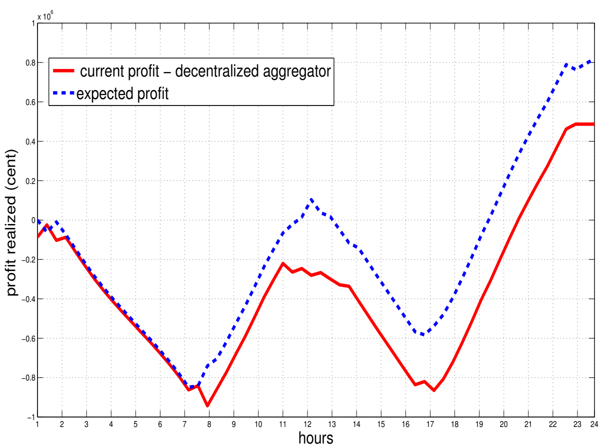

Figure 9. Decentralized aggregators, expected cost vs real cost.

Analogously, in Figure 9 the dashed curve represents the expected profit in the decentralized aggregator case at the end of day 3. That curve is given by the energy costs of the optimal profile of day 3 of the centralized aggregator. Notice that the difference between the expected gain and the actual gain of the aggregator in the decentralized case is greater than that of the centralized case.

V. CONCLUSION

This paper proposed the combination of reinforcement learning and optimization as a mechanism for buying/selling energy in a distributed power network. Simulations results showed that our approach is more efficient than the approach used in DEZENT. Next the paper study the effect of the aggregator on the distributed power market. The general aggregator concept is to make use of the flexibilities of the prosumers for providing active demand services in the power market. The results of the introduction of the aggregator in the distributed power grid have been the reduction of the peak energy consumption and the lowering of the electricity cost for the population of prosumers. Future works will include the development of a randomized algorithm that allow the prosumer to use different learning strategies for biding into the power market. At the optimization level, the repeated re-planning algorithm currently used by the prosumer will be extended in order to help minimize the mismatch between the anticipated energy profile and the real energy profile used during the day. Finally, the strategic interaction between prosumers will be studied through a dynamic games. Investigating on what happens if we are dealing with an infinite number of power prosumer in the distributed power grid.

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